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**SEALED-BID AUCTION OF DUTCH MUSSELS: STATISTICAL
ANALYSIS**

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Sealed-bid auction of Dutch mussels: statistical analysis

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Abstract

This article presents an econometric analysis of the many data on the sealed-bid auction that sells mussels in Yerseke town, the Netherlands. The goals of this analysis are obtaining insight into the important factors that determine the price of these mussels, and quantifying the performance of an individual purchase manager. Besides a case-study, the article is a general study on the role of auctions in supply chains and hedonic price factors.

Key words: supply chain, hedonic price, purchasing, econometrics, regression
JEL: C0, C1, C9

1 Introduction

In a *sealed-bid auction*, all buyers simultaneously submit their sealed bids; in case of a draw, the winner is the buyer who entered the highest price first (details follow in Section 4). Auctions are an important research topic; see recent publications such as Anandalingam and Raghavan (2005) and Katok and Roth (2004).

Auctions create transparent markets by concentrating demand and supply. A sealed-bid auction, however, provides bidders much less information on the behavior of other bidders. But sealed-bid auctions are fast; e.g. the Yerseke auction sells 30 lots in less than an hour (speed is essential because mussels are highly perishable and many small lots are sold). Note that a single mussel lot may cost as much as € 200,000.

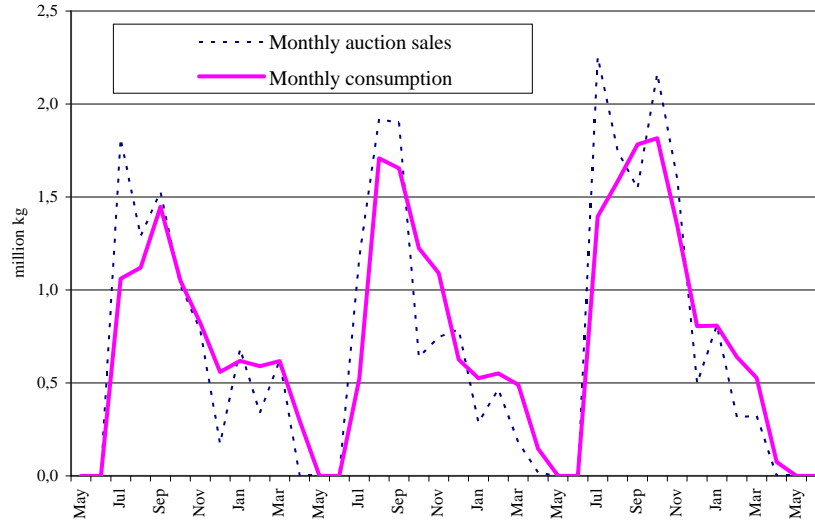


Fig. 1. Bullwhip effect in Dutch live-mussel supply chain

Furthermore, auctions (of whatever type) may play important roles in *supply chains*. Figure 1 shows that the well-known ‘bullwhip effect’ does occur in the mussel supply chain.

Dutch mussels are an important product: annually, between 50 and 100 million kilograms of raw mussels are delivered to the auction in Yerseke. Yerseke is the only mussel auction in the world. Most Dutch mussels are exported, mainly to Belgium and France.

In our case study, we address the following questions:

- Do auctions hurt big buyers; i.e., do companies that have big market shares need to purchase large quantities at higher prices? (Big buyers of vegetables, fruit, and flowers try to avoid auctions by pre-arranging prices with suppliers; in our case study, however, Dutch mussels can be bought at the auction in Yerseke only.)
- Does abundant supply decrease the auction price? The supply of products such as mussels is subject to the whims of mother nature.
- Do prices vary with the time of the year? Lee et al. (1997) discusses the bullwhip effect of seasonality. Indeed, in our case study the variation of monthly auction sales exceeds that of monthly consumption. Figure 1 shows data for ‘live’ mussels, which are used for immediate consumption (whereas ‘processed’ mussels are further treated in factories).
- Which factors determine the ‘hedonic’ price? This price is the implicit price of objectively measured characteristics of the product. The classic reference on hedonic prices is Rosen (1974). There are publications on the hedonic

prices of agricultural commodities such as cotton (Brown et al. 1995), wheat (Espinosa and Goodwin 1991), Christmas trees (Davis 1993), and tuna fish (McConnell and Strand 2000).

- Do different purchase managers get different prices? If that is the case, their companies should provide better training and decision support systems.

To answer these questions, we develop a linear regression model. We judiciously select explanatory variables and transformations that improve the fit of the model and make sense from the viewpoint of economic theory. To estimate the regression parameters (or coefficients) we use a database with measurements on 28,017 mussel lots traded in Yerseke during the years 1986/1987 through 1999/2000. Our model also provides the input for a decision support system (DSS) that we develop for the objective performance evaluation of a given individual purchase manager (such a manager may spend several million euros within an hour).

We have organized the remainder of this article as follows. In Section 2, we formulate four economic hypotheses for the questions raised above. In Section 3, we give details on the Dutch mussel industry. In Section 4, we describe the organization of the Yerseke mussel auction and the challenges faced by the purchase managers who are active at this auction. In Section 5, we specify our regression model, and discuss our data base and sample selection. In Section 6, we present the results of our estimated regression model, including tests of our four hypotheses. In Section 7, we investigate the predictive (instead of the explanatory) usage of our regression model. In Section 8 we develop a model to assess the performance of a specific purchase manager. In Section 9, we present our conclusions and possible topics for future research. More details about our study can be found in Van Schaik and Kleijnen (2007).

2 Four hypotheses

In this section, we formulate four hypotheses in the null form, as is standard in mathematical statistics. Consequently, we reject these hypotheses only if there is strong counter-evidence; i.e., the type-I error probability is only α where we select $\alpha = 0.05$. The alternative hypotheses simply negate the corresponding null-hypotheses.

Common sense may suggest that a big buyer pays a lower price because of his or her negotiating power. However, at a sealed-bid auction there is no bilateral negotiating, so buying power carries no weight. On the contrary, we expect that big buyers must bid higher to maintain their market shares. For example, a buyer with a 20% market share has to submit bids that lead to success in 20% of the cases, whereas a buyer with a 10% market share must bid with

only 10% success probability. This leads to the following null-hypothesis.

Hypothesis 1: companies with higher market shares pay the same price (for the same quality of mussels) as companies with lower market shares.

We also want to determine the price effect of total supply per ‘mussel year’, which starts toward the end of June and ends in April of next year.

Hypothesis 2: mussel prices do not vary with total annual supply.

Many commodities show seasonal price behavior; examples of such commodities are heating oil and agricultural products. Such variations in demand or supply cause volatile prices. If products can be stored for several months, fewer products will be purchased when prices are high—which decreases the price differences among months. In the Dutch mussel industry, supply and demand result in much higher prices in June, July, and August. However, the variable ‘meat yield’ (which affects the hedonic price) is also higher in these three months, so collinearity needs to be accounted for in our regression analysis.

Hypothesis 3: mussel prices do not vary with the time of the year.

A purchase manager has an important effect on his firm’s performance. Unfortunately, there is little systematic empirical evidence. We develop the following three-step method to assess a purchase manager’s performance:

- (i) Develop a theoretical price model, based on our regression model. This model accounts for all objective characteristics of the mussel lot and the circumstances under which it is bought.
- (ii) Calculate the difference between the theoretical and the actual prices.
- (iii) Compare the premium paid by a particular purchase manager with the premiums paid by other purchase managers.

Hypothesis 4: all purchase managers have the same performance level.

3 The Dutch mussel industry

Worldwide, the mussel industry is thriving—from Norway to South Africa and from the United States to China. The major producing countries are Spain and China. In the Netherlands, approximately eighty ships harvest and transport mussels, cultivated on the seabed. Mussel ‘farmers’ rent part of the bottom of two North Sea estuaries in the Netherlands—namely the Wadden Sea (or Dutch Shallows, from now on called Wadden) in the North of the country and

the Eastern Scheldt (from now on called Scheldt) in the South-West—which are a few hundred kilometers apart.

After the mussels have been transported to Yerseke and sold, they are placed in special plots in the Scheldt. These plots serve as wet storage for this highly perishable produce. From these plots, mussels are harvested on demand. There are two types of demand: (i) live mussels and (ii) processed mussels. The former type account for 84% of the mussels, on average. The live-mussel companies clean, grade, and pack mussels. Their purchasing costs amount to approximately 60% of turnover. These mussels must have higher quality than the processed mussels. The mussel-processing factories transform raw mussels into either frozen mussels or mussel preserves. Their purchasing costs are approximately 40% of turnover, so more value is added to processed mussels than to live mussels.

Actually, these percentages for live versus processed mussels vary from year to year—according to the quality and quantity of supply. When supply is abundant in a given mussel year, then prices are low and large quantities are processed; e.g., in 1998 26% (instead of the usual 16%) was frozen and preserved.

4 The Yerseke auction

The mussel farmers ship the mussels to Yerseke, a town on the Scheldt. The farmers display their mussels in the harbor at the auction house—called the House in this article. The House supplies a crucial service, namely quality control. So—before the auction—employees of the House inspect the mussels in the ships, and provide information on each lot’s quality to the purchase managers.

All purchase managers are physically present at the auction, and simultaneously submit their sealed bids by entering a price on their individual keyboards linked to a central computer. The House publicly announces the end of the bidding time, and the computer then displays the price of the highest bid and the name of the buying company. Details on the lower bids are not revealed. In case of a draw, the winner is the buyer who entered the price first.

There is a minimum or reservation price that is fixed for one year; e.g., this price was € 16 per ‘mussel ton’ (100 kilograms) in 1999. If no buyer bids above the minimum price, then the House buys the lot at that price. At the end of the mussel year, the House auctions these mussels in the usual way. Actually, only 1.6% of all the lots that we analyze was sold at this minimum price.

All mussels supplied by a farmer in one ship are usually auctioned as one *lot*. However, the House may decide to auction each of the two or three holds of the ship as separate lots. In times of great price volatility, this practice might spread the risk for the farmer. Indeed, lots appear at the auction in a random sequence because there may be a drift in price setting during the auction session (e.g., a buying frenzy may cause such a drift).

Note that the anomaly of different prices for identical lots has been widely investigated in the literature. For example, in a study of wine auctions, Ginsburgh (1998) argues that it is unlikely that a bidder's valuation would differ for identical lots of wine, saying that 'a rosé is a rosé is a rosé'. Van den Berg et al. (1999) investigates a flower auction, and assumes as well that 'a rose is a rose is a rose'.

All eighty Dutch mussel farmers sell all their produce through the House. Occasionally, the House also sells the produce of German mussel farmers. The number of buyers varies slightly over the years, due to companies closing down, starting up, or merging. There are on average twenty buyers for live mussels, and four buyers for processed mussels. Sellers and buyers pay a fee to the House, namely a percentage of their sales and an amount per mussel ton.

Lot sizes are measured in mussel tons. However, it is not practical to measure the weight of an individual lot directly. Instead, it is assumed that seven tons go into one cubic meter. The cubic capacity of a ship was carefully measured when the ship was built. Hence, the content of a particular lot is determined as a percentage of the ship's full cubic capacity. The weight estimated in this manner is the gross tonnage. The buyer pays only the net tonnage, which is gross tonnage minus 'impurity'. Impurity consists of loose shells, starfish, dead or damaged mussels, seed mussels (i.e., mussels shorter than 30 millimeter), and other shellfish and crustaceans such as crabs. This impurity is measured as a percentage of gross tonnage (impurity is an explanatory variable in our regression model, as we shall see).

Altogether, the House collects the following data for the potential buyers: meat yield, size count, impurity, barnacles, and slippers. The House does not collect data on color, taste, and texture of mussels; the buyers themselves can see the color, taste some mussels, and determine the texture. The variables that are not measured by the House, plus any other variables that might affect the price are represented by the 'noise' or 'disturbance' term in the regression model (as we shall see).

A buyer faces the following problems at the auction. (i) A lot consists of a great variety of mussels: some lots consist largely of small mussels, other lots consist of large mussels, etc. So there are never lots of only one mussel size. The consumer, however, is supplied with only five sizes of mussels—sorted

according to shell width. (ii) Lots are auctioned sequentially, so the buyer cannot simply optimize the combination of lots to be bought. The buyer must wait to see whether his bid price turns out to be the highest price so he does purchase that lot and realizes his desired market share.

The House computerized its process in 1986. Before an auction session starts, the House compiles an information sheet about the lots. This sheet displays the lot's quantity, farmer, origin, and various quality indicators (see Table 1 below). After the auction session, the House completes this sheet by adding the price per lot and the name of the highest bidder. This sheet is immediately distributed to sellers and buyers.

5 Regression model specification

To determine hedonic prices, Rosen (1974) proposes linear regression analysis with independent variables that affect this price. In general, such a model may be written as

$$y = \beta_0 + \sum_{j=1}^k \beta_j x_j + e. \quad (1)$$

In our case study, the variable to be explained is the price per mussel ton (say) p . In model (1), we use the dependent variable $y = \ln(p)$, for two reasons: (i) The marginal effect $\partial y = \partial \ln(p) = \partial p/p$ is the *relative* price change, so we remove the scale effects caused by choosing a particular currency such as euros or dollars. (ii) Some original explanatory variables z_j are measured as real numbers and for a subset of these variables we use their logarithm so the explanatory variable becomes $x_j = \ln(z_j)$; for these explanatory variables the regression parameter β_j denotes the elasticity coefficient $(\partial p/p)/(\partial z_j/z_j)$, which is popular in economic theory.

However, some original variables are measured as real numbers, and yet we are not interested in their elasticity coefficients. For example, for barnacles (measured by z_8 ; see Table 1) we wish to estimate the relative price change as that variable changes by an absolute value:

$$\ln(p) = \dots + \beta_8 z_8 + \dots \text{ so } (\partial p/p)/\partial z_8 = \beta_8 \text{ or } \partial p/p = \beta_8 \partial z_8.$$

Notice that there may be zero barnacles in a lot, so the logarithmic transformation would not apply anyhow. Actually, we studied various scatter plots to decide whether logarithmic transformations provide a better-fitting regression model.

Some other variables are not measured as real numbers but are *binary* variables. For example, z_{11} equals 1 if the mussels originate in the Wadden, and

Variable (subscript)	Expected sign	Definition
Price		Price in Dutch guilders per mussel ton of net tonnage
Market share (1)	+	Quantity bought by given buyer in given mussel year divided by quantity bought by all buyers
Annual supply (2)	-	Total quantity for sale at the auction during one mussel year
Season (3)	+	Day of mussel year, starting at day 1 of mussel year
Buyer performance (4)		1 for purchase manager being assessed; otherwise 0
Meat yield (5)	+	Percentage mussel meat in mussel raw material.
Size count (6)	-	Number of mussels contained in 2.5 kg raw material
Impurity (7)	-	Everything that is not mussel, as a percentage of gross tonnage
Barnacles (8)	-	Barnacles attached to mussels, in grams per 2.5 kg raw material
Slippers (9)	-	Slippers attached to mussels, in grams per 2.5 kg raw material
Usage (10)	+	1 for live mussels; 0 processed mussels
Origin (11)	+	1 for Wadden mussels; 0 for Scheldt mussels
Trend (12)	+	Year in which lot is offered for sale

Table 1

Regression variables, expected signs, and definitions

0 if the mussels originate in the Scheldt. (Mathematically, $\ln 0$ is undefined; economically, an elasticity coefficient for origin is nonsense.) The coefficient of a binary variable is the estimated percentage change in price when the lot has the characteristic described by the binary variable while all other characteristics are constant; e.g., Wadden mussels are β_{11} percent more expensive than Scheldt mussels.

Table 1 provides the definitions (and the predicted signs) of our regression variables. We specify three types of explanatory variables:

(i) For the variables market share, supply, season, meat yield, size count, and impurity we estimate elasticity coefficients through a double-log transformation:

$$\beta_j = \frac{\partial p/p}{\partial z_j/z_j} \text{ if } j = 1, 2, 3, 5, 6, 7. \quad (2)$$

(ii) For the variables barnacles, slippers, and trend we estimate relative price changes when these variables change by an absolute amount—using a single-log transformation:

$$\beta_j = \frac{\partial p/p}{\partial z_j} \text{ if } j = 8, 9, 12. \quad (3)$$

(iii) For the three variables ‘specific buyer’, ‘use as live mussel’, and ‘origin’, we use binary variables. For example, for $z_{11} = 1$ the regression model in (1) gives $\ln p = \beta_0 + \beta_{11} + \dots$ or $p = \exp(\beta_0 + \beta_{11} + \dots)$, whereas $z_{11} = 0$ gives $\ln p = \beta_0 + \dots$ or $p = \exp(\beta_0 + \dots)$ so the price ratio is $\exp(\beta_{11})$. In general, the relative price increase is

$$\frac{\partial p}{p} = e^{\beta_j} - 1 \text{ if } j = 4, 10, 11. \quad (4)$$

Finally, the term e in model (1) represents the noise caused by our exclusion of some explanatory variables. For example, the House does not measure the mussels’ color, taste, or texture; neither does the auction measure the potential buyers’ utility functions. We assume that e is either white noise or autocorrelated noise. White noise means that e is Normally, Independently, and Identically Distributed (NIID); autocorrelated noise means that the independence assumption does not hold.

In our regression model, we include most (but not all) of the information that the House gives to the buyers, before the auction starts; i.e., we exclude some of the House’s information. Our reason is that reducing the number of independent regression variables increases prediction performance (also see the Adjusted R^2 in Section 6). So, we use size count but not shell width and length, even though the latter two variables are displayed in the information sheet that the House distributes to sellers and buyers.

Besides, the information supplied by the House to potential buyers, we include some more independent regression variables, namely *control* or *concomitant* variables. We distinguish four types of control variables:

- The following five variables control quality, so they affect the hedonic price.
Meat yield (z_5): the consumer is interested in the amount of mussel meat. The auction estimates this percentage from a sample from each lot.
Size count (z_6): size count is determined by counting the number of mussels

per 2.5 kilograms net. Because smaller mussels are cheaper, we expect that a higher size count reduces the price; see the Expected Sign in Table 1.

Impurity (z_7): we have already discussed impurity in Section 4.

Barnacles (z_8): barnacles cause extra wear on the processing machines. The buyers' sorting machines categorize mussels according to shell width, so the machines may erroneously categorize small mussels with barnacle growth as large mussels. Barnacles also make mussels look less attractive to consumers. Slippers (z_9): slippers are animals that grow on mussels like barnacles do. Slippers create the same problems as barnacles do.

- Product usage (z_{10}) is a binary variable that denotes usage as either live mussels or processed mussels. All lots are listed by the House in the order of the ship's arrival at the harbor. As we have already mentioned (Section 4), these lots are traded in a random order so mussels intended for either live-mussel production or preserves are auctioned in a mixed order.
- Origin (z_{11}) may be important because soil characteristics can affect the flavor of mussels. In practice, the average price of Wadden mussels is higher. However, these mussels also tend to be heavier (z_6) and meatier (z_5), so a collinearity problem may arise. Origin measures whether Wadden mussels generate a premium, even if we control for characteristics such as meat yield and size count.
- The trend variable (z_{12}) is measured such that, e.g., its value 86 denotes the mussel year from June 1986 through April 1987. Besides seasonal price movements (see z_3), there has been an increasing price trend over the years. Trend elements are inflation in general and a considerable rise in the demand for mussels without a noticeable increase in supply. This price increase has mostly benefited the mussel farmers, because the bottleneck in the supply chain is the areas where mussel farmers cultivate mussels; live-mussel traders and mussel-processing factories have excess capacity.

We obtain data on all the 30,303 lots traded at the House during 1986/1987-1999/2000. Next, we remove a number of lots because they are not representative; i.e., some fishing and purchasing companies belong to the same group, and trade produce at the auction at pre-arranged prices. Our correction reduces the number of lots to 28,017.

Not all variables have the same *sample size*. The variables z_5 through z determine the hedonic price, and are measured for each of the 28,017 lots; and so is z_4 (buyer performance) measured for each lot. Obviously, Supply (z_7) and Trend (z_{12}) are measured per year, so we have only fourteen observations. Market share (z_1) is measured per year and per buyer, so the number of observations is approximately $14 \times 24 = 336$. Season (z_3) also has fewer observations: we denote the first day of a specific season by the integer 1, the next day by 2, etc.

Explanatory variable (j)	OLS: $\widehat{\beta}_j$	$t(\widehat{\beta}_j)$	GLS: $\widetilde{\beta}_j$	$t(\widetilde{\beta}_j)$	Standardized: $\widetilde{\gamma}_j$
Constant (0)	6.9806	78.85	7.0785	59.08	
Market share (1)	0.0421	17.81	0.0343	19.57	0.0795
Annual supply (2)	-0.8396	-91.93	-0.8473	-49.65	-0.2127
Season (3)	-0.1586	-78.56	-0.1474	-40.81	-0.1666
Meat yield (5)	0.8147	55.39	1.1046	76.07	0.3659
Size count (6)	-0.8748	-85.92	-1.0526	-107.12	-0.4533
Impurity (7)	-0.1412	-27.89	-0.1728	-43.08	-0.1784
Barnacles (8)	-0.0005	-9.02	-0.0011	-24.66	-0.1063
Slippers (9)	-0.0007	-6.31	-0.0003	-3.83	-0.0164
Usage (10)	0.1975	32.41	0.0916	19.19	0.0835
Origin (11)	-0.0339	-6.16	-0.0581	-10.21	-0.0511
Trend (12)	0.0414	75.22	0.0418	40.19	0.1708
Durbin-Watson statistic	0.954		2.290		
Adjusted R^2	0.66		0.56		

Table 2

Regression results

6 Regression results

We compute our regression results through SPSS, version 9.0. In Table 2 the second column shows the estimated regression coefficients $\widehat{\beta}_j$ in model (1) when using Ordinary Least Squares (OLS). It is well-known that these estimates are ‘best’ if the white-noise assumption holds; i.e., the $\widehat{\beta}_j$ ($j = 1, \dots, k$) are the minimum-variance unbiased linear estimators. The interpretation of $\widehat{\beta}_j$ varies with the explanatory variable; see (2) through (4) (relative, absolute, binary changes). We first estimate our model without the binary variable for buyer’s performance (z_4), because we wish to validate our model before we apply it to test hypothesis 4 (purchase manager’s performance).

The table does not display $\widehat{cov}(\widehat{\beta}_j, \widehat{\beta}_{j'})$, the estimated covariances for the pair j, j' of estimated regression coefficients ($j, j' = 1, \dots, 12$). These covariances are not zero, because some explanatory variables are correlated. The table indirectly displays $\widehat{cov}(\widehat{\beta}_j, \widehat{\beta}_j) = \widehat{var}(\widehat{\beta}_j)$, the estimated variances, because the table does display Student’s t statistic, per regression coefficient: $t(\widehat{\beta}_j) =$

$\widehat{\beta}_j / [\widehat{var}(\widehat{\beta}_j)]^{1/2}$. All 12 t statistics are significant at any reasonable α value, even at $\alpha = 0.001$. One explanation is that the number of observations for variables measured per lot is extremely high (namely, 28,017).

These t statistics, however, assume white noise, whereas the table displays a Durbin-Watson statistic equal to 0.954 (see the next-to-last row), which indicates positive autocorrelation. We therefore switch to *Generalized Least Squares* (GLS), assuming the noise follows a first-order autoregressive process. To compute the GLS estimates $\widetilde{\beta}_j$, we use SPSS's Prais-Winsten method. The autocorrelation coefficient is estimated to be 0.5826 with a standard error of 0.0049 (not displayed). This GLS gives an acceptable Durbin-Watson statistic of 2.290. The GLS estimates $\widetilde{\beta}_j$ are close to the OLS estimates $\widehat{\beta}_j$ (both estimators are unbiased, so they have the same expected value β_j). Comparing the t values for GLS and OLS shows that the GLS values are smaller for some coefficients, but not for all.

To compare the relative effects of the explanatory variables, we use the *standardized* regression coefficients (say) $\widetilde{\gamma}_j$ defined as follows (also see Kleijnen and Helton 1999):

$$\widetilde{\gamma}_j = \frac{\widetilde{\beta}_j \sqrt{\widehat{var}(x_j)}}{\sqrt{\widehat{var}(y)}} \quad (j = 1, 2, 3, 5, \dots, 12).$$

These $\widetilde{\gamma}_j$ are displayed in the last column of the table. They suggest that the most important variables are supply, size count, season, trend, and meat weight; the least important variables are barnacles, origin, and slippers.

Last but not least, the overall explanatory power of the model is reasonable: the Adjusted R^2 is 66% for OLS and 56% for GLS (see last line of table). Other regression models for hedonic prices gave only 37% for Christmas trees and 64% for tuna fish—but 89% for wheat, and 93% for cotton; see the references in Section 1. Switching from OLS to GLS decreases the Adjusted R^2 ; nevertheless, GLS gives better predictions as we shall see in Section 7. Note that R^2 is a popular but possibly misleading statistic; see Kleijnen and Deflandre (2002) and Sutton (1990).

Now we return to testing the four hypotheses formulated in Section 2. Table 2 shows that market share (z_1) has a significant positive effect on price; i.e., big buyers tend to bid high. So we reject Hypothesis 1 at the 0.001 level.

Supply (z_2) has a significant negative effect, which confirms the negative slope of the demand function that is usually postulated in economic theory. Nevertheless, we find the size of this effect surprising: the elasticity coefficient is -0.8.

Season (z_3) has a significant effect on the mussel industry, so we reject Hypothesis 3. Our interpretation is that the buying companies start the season without any raw mussels in stock, so they quickly build stocks up to normal working levels; apparently, in that short period of time (approximately six weeks) supply cannot keep up with demand.

Buyer performance (z_4) can be included as a binary variable that denotes whether a particular manager buys a specific lot (see again the definitions in Table 1). We can then test whether its regression coefficient is significantly different from zero. We reject Hypothesis 4 at the 0.001 level (not displayed in Table 2). We shall further investigate buyer performance in Section 8.

The estimated effects of the control variables z_5 through z_{10} show the expected signs. And there is the expected long-term increase in price; see z_{12} .

However, the effect of origin (z_{11}) is significantly negative; i.e., our regression model predicts that Wadden mussels are less expensive (see the definition of z_{11} in Table 1). In practice, Wadden mussels tend to be more expensive than Scheldt mussels. Our model, however, also controls for quality and season, measured by meat yield (z_5) and size count (z_6), on which Wadden mussels generally outperform Scheldt mussels. In reality, after the period of reproduction (May and June), Wadden mussels reach the minimum quality requirements earlier. So, at the beginning of the mussel year—when demand is high because companies want to build up stocks—most mussels sold are Wadden mussels. However, buyers do not pay a higher price simply because mussels originate from the Wadden: they pay a higher price for Wadden mussels because these mussels have better quality and many Wadden mussels are sold at the very beginning of the mussel year when demand is high. Wadden prices may actually be lower because of the larger distance between the Wadden and Yerseke. Indeed, it may take a ship up to eighteen hours to travel this distance, which shortens shelf life considerably: in hot weather, the journey may kill up to 5% of the mussels on board the ship. We conclude that origin is important, but in a way that violates our *a priori* expectation.

We also investigate the *robustness* of the preceding regression results, as follows. We estimate a new regression model for each of the fourteen years for which we have data. We find that the individual regression estimates do not change much over these fourteen years.

7 Predictive performance of regression model

In this section, we investigate the predictive performance of our regression model. We therefore eliminate the most recent year (1999/2000) in our data

base, and re-estimate our model from the subsample covering the remaining thirteen years. We use this re-estimated model to predict the eliminated year; i.e., we predict the price of the 2,199 lots auctioned during 1999/2000.

This prediction gives the following descriptive statistics for the actual and predicted prices. The standard deviation of the predicted prices is lower and the range is narrower. This smaller range results from a lower maximum price and a higher minimum price. This minimum is slightly higher than the House's minimum price (described in Section 4). Our explanation is that our model does not account for all variations that occur in practice; i.e., its Adjusted R^2 is smaller than one.

When predicting the price of an individual lot, we account for *autocorrelation*. So when the preceding lot has an actual price p that exceeded the estimated price \hat{p} , then we increase our predicted price for the current lot (say) t with $t = 1, \dots, 2199$:

$$\ln(\widehat{p}_t) = \widehat{\beta}_0 + \sum_{j=1}^{12} \widehat{\beta}_j x_{j;t} + \frac{\widehat{\lambda} \ln(\frac{p_{t-1}}{p_{t-1}}) + \widehat{\lambda}^2 \ln(\frac{p_{t-2}}{p_{t-2}}) + \widehat{\lambda}^3 \ln(\frac{p_{t-3}}{p_{t-3}}) + \dots + \widehat{\lambda}^{t-1} \ln(\frac{p_1}{p_1})}{\widehat{\lambda} + \widehat{\lambda}^2 + \widehat{\lambda}^3 + \dots + \widehat{\lambda}^{t-1}}$$

where the first two terms follow from (1) through (4) with $x_{j;t}$ denoting the value of the explanatory variable j for lot t ; the remaining terms make the weights of older prediction errors decrease geometrically, the sum of the geometric weights being one. To explain this model, we consider the following simple example: let's assume that all past lots with important weights have the same relative prediction error (say) 10%; we then increase our prediction for the current lot by the same percentage. Notice that we quantify the explanatory variable $x_{j;t}$ per lot, per season, or per year.

To derive the formula for the absolute price, we use the first two terms of the equation above, combined with (1) through (4) and the GLS estimates in Table 2. The mean and the median of the predicted prices \hat{p} turn out to be higher than the actual values p (obviously, $E[\ln(p)] \neq \ln[E(p)]$). The individual \hat{p}_t and p_t give the following regression line:

$$\ln(\hat{p}) = 1.559 + 0.675 \ln(p) \quad (5)$$

with $R^2 = 0.54$, computed from 2,199 lots. So the intercept is positive and the slope is smaller than one—as is to be expected, even if the model is correct; see Kleijnen, Bettonvil, and Van Groenendaal (1998).

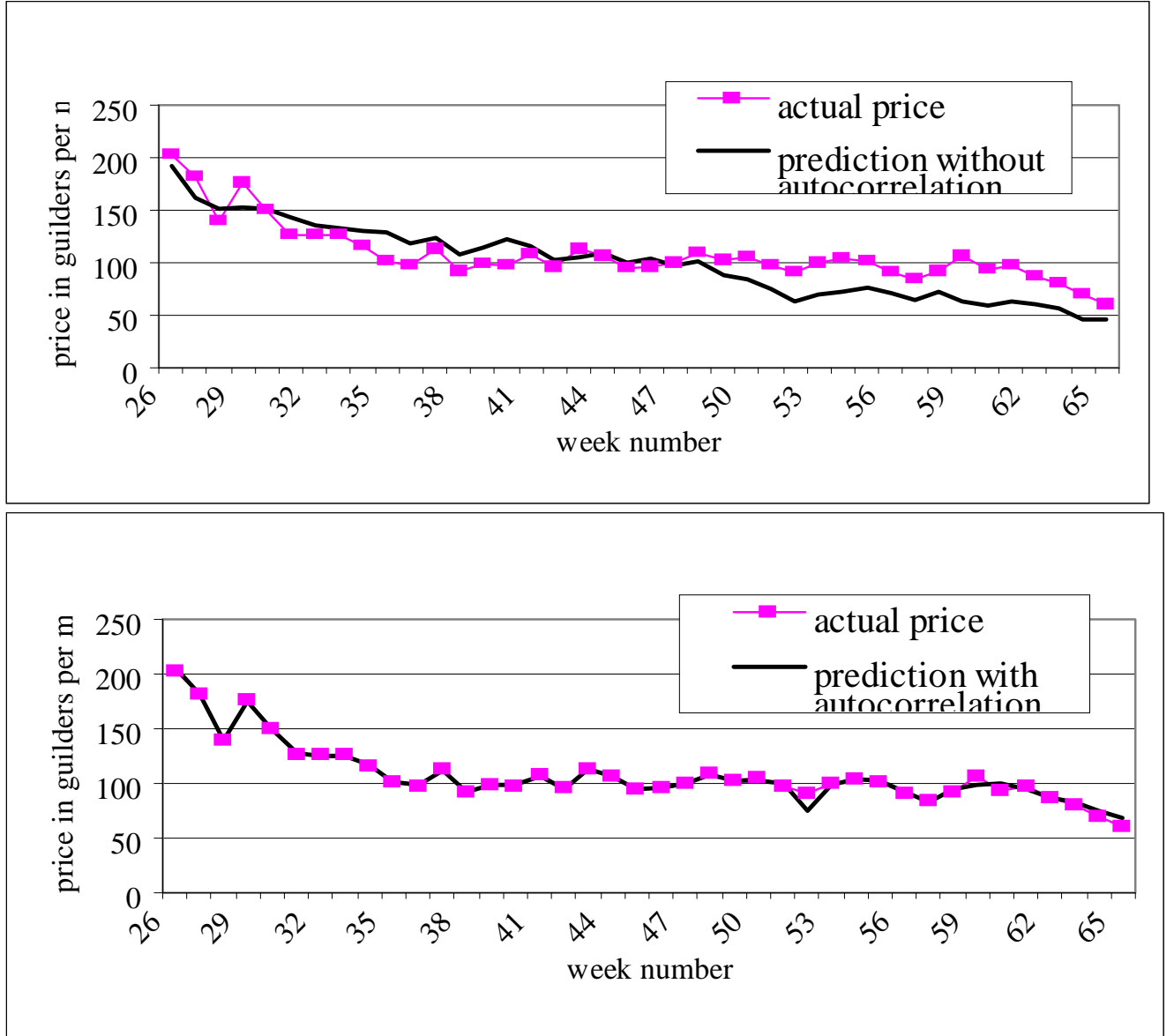


Fig. 2. Prediction accuracy of GLS with autocorrelation and OLS

For the non-transformed variables, (5) gives

$$\hat{p} = e^{1.559} p^{0.675} = 4.75 p^{0.675}.$$

The performance of our predictor improves considerably if we account for autocorrelation.; see Figure 2, which displays the weekly averages of the actual prices for GLS with autocorrelation. and OLS respectively.

Finally, we investigate whether our model is suitable for computer-supported buying. An example would be: buy 20% of all lots to be auctioned in 1999/2000 (without intentional bias for any characteristic; i.e., the computer is not told to

Explanatory variable (j)	Effect $\widetilde{\beta}_j$	Overall mean \bar{x}_j	Buyer mean $\bar{x}_j z_4 = 1$	Price difference $\partial\widehat{p}$ $\widetilde{\beta}_j[(\bar{x}_j z_4 = 1) - \bar{x}_j]$	Relative price $\partial\widehat{p}/\widehat{p}$
Market share (1)	0.0343	1.8475	2.2161	0.0127	1.27%
Usage (10)	0.0916	0.8396	1.0000	0.0147	1.48%
Company characteristics					2.77%
Meat yield (5)	1.1046	3.2621	3.3183	0.0620	6.39%
Size count (6)	-1.0526	4.9288	4.8902	0.0407	4.16%
Impurity (7)	-0.1728	2.9815	2.8584	0.0213	2.15%
Barnacles (8)	-0.0011	17.5835	15.6651	0.0020	0.20%
Slippers (9)	-0.0003	6.7544	4.0686	0.0008	0.08%
Origin (11)	-0.0581	0.4963	0.4808	0.0009	0.09%
Mussel quality					13.62%
Annual supply (2)	-0.8473	4.4098	4.4369	-0.0230	-2.27%
Trend (12)	0.0418	92.6692	95.1552	0.1039	10.95%
Season (3)	-0.1474	4.1373	3.9660	0.0253	2.56%
Timing					11.21%
Theoretical price					29.86%
Actual price					37.81%
Premium paid by buyer					6.12%

Table 3

Buyer performance assessment

purchase, say, meaty mussels). We compute that in the preceding period 1986 through 1998, the estimated 20% quantile of the differences between actual prices and their predictions is -23.64. We therefore enter a bid equal to the model's predicted value minus 23.64. The computer turns out to buy 385 lots (or 18%) of the 2,199 lots auctioned during 1999/2000, whereas a normally distributed and unbiased estimator has a 50% chance of underestimating the true value. So, our model needs only minor calibration to make it suitable as a DSS for computer-assisted buying. Our model, however, ignores the influence that such a DSS might have on its competitors' bidding behavior.

8 Buyer performance

In this section, we develop a new tool for measuring the performance of an individual purchase manager (also called a ‘buyer’). The ‘bottom line’ question is (see the bottom right-hand corner of Table 3): why did this manager pay 6.12% more than the predicted price?

We start with columns 1 and 2 of Table 3. These columns reproduce columns 2 and 4 of Table 2—but in a different order, and inserting a few extra rows (e.g., ‘Company characteristics’). These extra rows account for the characteristics of this buyer’s company, his mussel quality, and his timing—as follows.

The first row of numbers shows that $\bar{x}_1 = \ln(\bar{z}_1) = 1.8475$. So, the price-elasticity definition in (2) implies $\hat{p} = \hat{\beta}_1 \ln(\bar{z}_1) = 0.0343 \times 1.8475 = 0.06337$. The market share for this buyer gives $\bar{x}_1 = \ln(\bar{z}_1 | z_4 = 1) = \ln(2.2161) = 0.7958$. Hence, the predicted price difference caused by market share differences is $\partial \hat{p} = \hat{\beta}_1 (\ln(\bar{z}_1) - \ln(\bar{z}_1 | z_4 = 1)) = 0.0343 \times (1.8475 - 0.7958) = 0.0359$. This 0.0359 gives a price increase of $\exp(0.0359) - 1 = 0.0366 = 3.66\%$. So, this manager pays 3.66% more because he works for a large company.

The following rows can be explained analogously. For example, the next row shows that this manager works for a company that uses live mussels instead of processed mussels, which explains that he pays 1.48% more than average.

Further, he buys mussels of good quality and therefore pays 13.62% more than average; we distinguish six quality characteristics, from meat yield to origin.

This manager bought when there was a good supply of mussels, and therefore paid 2.27% less than average. However, he did not start in 1986, but only when the trend had already increased prices: 10.95% price effect. He bought early in the season when prices were 2.56% higher (live-mussel buyers cannot wait as long as mussel-processing factories can).

All in all, this manager is expected to pay 29.86% more—given his company’s characteristics, his mussel quality, and his timing.. Actually, he paid 37.81% more. He should explain why he paid 6.12% more!

Note that this 6.12% is significant: if we add the explanatory variable z_4 to the GLS model in Table 2, then we find a regression coefficient of 0.0939—which is significantly different from zero at the 0.001 level because $t = 10.94$.

Nevertheless, our assessment of this buyer is only tentative, for at least the following two reasons.

- The GLS model has an Adjusted R^2 of no more than 56% (see Table 2);

only under the assumption of a perfectly valid regression model does the statistical significance of $\widetilde{\beta}_4$ hold.

- The buyer obtained high-quality mussels, which costs him 13.62% extra. On one hand, this quality is justified if his company really needs this quality to keep its customers satisfied. On the other hand, his company may be shipping excellent mussels, whereas its customers are willing to pay for average quality only. Indeed, for mussels (and other agricultural products) customers do not always get exactly the quality they ordered. In this type of business, the ability to deliver the exact quality ordered by customers is probably a critical success factor.

We might refine our analysis in Table 3, in which we compare the performance of a specific purchase manager with the mean performance of all the purchase managers at the auction. For example, it might be more appropriate to compare a particular manager who buys (say) *live* mussels, with the average live-mussel buyer. In that case, we would estimate the regression coefficients for the more homogeneous subsample consisting of all live-mussel buyers excluding this particular manager. Similarly, we might compare the performance of a manager of a large firm with a subsample consisting of large firms only.

In summary, whichever model we use to assess buyer performance, a particular purchase manager might argue that the model is only an approximation of reality. For example, he may pay more than his competitors because he buys mussels that score better on characteristics not included in our model, such as color, taste, and texture. Nevertheless, he would then have to explain why he is willing to pay more for these characteristics and why he thinks his customers are willing to pay for these characteristics while his competitors' customers are not. Ultimately, this manager's justification would have to be judged by professionals.

9 Conclusions and further research

In this article, we investigated the sealed-bid auction for mussels at Yerseke, the Netherlands. We formulated four null-hypotheses that we based on basic economic theory. We rejected these hypotheses, and derived the following conclusions:

- Large buyers pay higher prices (to maintain their market share?).
- The price/supply elasticity coefficient is surprisingly high, namely -0.8.
- Season is important.
- Purchase managers perform significantly differently from each other.

Moreover, whereas in practice Wadden mussels fetch higher prices, our model suggested that these higher prices are not caused by the origin itself, but by the concomitant quality characteristics and the season.

To derive these conclusions, we specified a linear regression model, including double-logarithmic and single-logarithmic transformations and binary explanatory variables. We estimated the regression coefficients through data extracted from a database with 28,017 mussel lots. These estimated coefficients have the correct signs.

Moreover, we developed a new DSS for the objective measurement of the performance of purchase managers. This DSS enables its users to find out whether a specific manager ‘underperforms’; i.e., in his efforts to buy lots that he thinks his company needs, he overshoots his target.

Further research is needed to remove the following limitations of our research.

- Only successful bids are included in our database; i.e., the data base does not contain offers by all the other potential buyers who were outbid. This limitation is typical of sealed-bid auctions.
- We concluded that big companies are at a disadvantage when making sealed bids. Our conclusion may not be valid for other industries than the Dutch mussel industry. Actually, all lots offered at the Yerseke auction are so small that any bidder can afford to buy any single lot. However, in (for example) the building industry, not all companies are large enough to carry out a specific large building project.
- Our model does incorporate most characteristics that are shown on the House’s information sheet used by the potential buyers. However, future research might also consider characteristics (such as color, taste, and texture) that are not listed on this sheet.
- Other methods of statistical analysis might be applied; e.g., tobit analysis (because of the censoring caused by the minimum price).
- Experimental economics and game theory provide different methodologies to study auctions.
- The requirements for the successful introduction of futures in mussels—in addition to spot markets—are a challenging research topic.
- Our DSS for measuring buyer performance may be extended through a Data Envelop Analysis (DEA), distinguishing between live and processed mussels, and between small and large mussels.
- Prices vary during the day; e.g., prices may decline during the day, as buyers realize their target purchase and withdraw from the market during the remainder of the day. These dynamics are not included in our regression model.

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